

VU Research Portal

Encouraging physical activity via a personalized mobile system

Klein, M.C.A.; Manzoor Rajper, A.; Middelweerd, A.; Mollee, J.S.; te Velde, S.J.

published in

IEEE Internet Computing
2015

DOI (link to publisher)

[10.1109/MIC.2015.51](https://doi.org/10.1109/MIC.2015.51)

document version

Version created as part of publication process; publisher's layout; not normally made publicly available

document license

Unspecified

[Link to publication in VU Research Portal](#)

citation for published version (APA)

Klein, M. C. A., Manzoor Rajper, A., Middelweerd, A., Mollee, J. S., & te Velde, S. J. (2015). Encouraging physical activity via a personalized mobile system. *IEEE Internet Computing*, 19(4), 20-27. [7096873]. <https://doi.org/10.1109/MIC.2015.51>

General rights

Copyright and moral rights for the publications made accessible in the public portal are retained by the authors and/or other copyright owners and it is a condition of accessing publications that users recognise and abide by the legal requirements associated with these rights.

- Users may download and print one copy of any publication from the public portal for the purpose of private study or research.
- You may not further distribute the material or use it for any profit-making activity or commercial gain
- You may freely distribute the URL identifying the publication in the public portal ?

Take down policy

If you believe that this document breaches copyright please contact us providing details, and we will remove access to the work immediately and investigate your claim.

E-mail address:

vuresearchportal.ub@vu.nl



Encouraging Physical Activity via a Personalized Mobile System

A large proportion of the Western population doesn't meet the guidelines of being moderately to vigorously active for at least 30 minutes five days a week. Here, the authors present a mobile system that goes beyond existing (mobile) physical activity interventions. Combining theory and evidence-based behavior-change techniques with a model-based reasoning system provides the right support and strategies at the right time for obtaining a physically active lifestyle.

Michel C.A. Klein
VU University Amsterdam

Adnan Manzoor
VU University Amsterdam

Anouk Middelweerd
VU University Medical Center

Julia S. Mollee
VU University Amsterdam

Saskia J. te Velde
VU University Medical Center

Engaging in sufficient physical activity has several beneficial effects on physical and mental health,^{1,2} while low levels of physical activity have been associated with increased risks for cardiovascular diseases, cancer, diabetes, and mental illness.³ Despite this, a large proportion of the Western population doesn't meet the guidelines of being moderately to vigorously active for at least 30 minutes five days a week.⁴ Therefore, physical activity promotion is a priority in most Western countries, with a need for cost-effective interventions.

To address this need, here we present the design of a mobile system, called *Active2Gether*, which aims to go beyond existing (mobile) physical activity interventions. To do so, our method combines theory and evidence-based behavior-change techniques (for example, goal setting) with modern technology (for example, sensor data interpretation and

predictive modeling), to not only address personal factors such as motivation but also social environment factors like social support. Based on our ongoing research on effective components for promoting (technology-mediated) physical activity, we describe the elements and structure of a personal and intelligent system that provides personally relevant support for obtaining a physically active lifestyle.

Background

It's widely believed that mobile technology can help in supporting health in general and promoting physical activity specifically. One of the main reasons for this belief is that mobile technology provides a good infrastructure for personalizing and tailoring the intervention. We can monitor people continuously and give feedback messages at any moment in time, taking the specific context into account.

Despite the popularity of wearable activity monitors and physical activity apps for smartphones, little is known about their effectiveness. In current mobile interventions, apps are mainly used as a supplemental tool in the main intervention to send reminders, track personal goals, or provide feedback. Studies report promising results, yet recent reviews indicate that physical activity apps don't make optimal use of existing effective behavior-change techniques and aren't theory-based.⁵ Furthermore, the social environment is hardly incorporated or addressed in such physical activity apps, even though it's believed to play an important role in motivating healthy behavior. Top-ranked apps mainly provide instructions on performing the behavior (66 percent of apps), demonstrate the behavior (53 percent), provide feedback on the performance (50 percent), and help set goals (38 percent).⁶ Thus, apps most often provide information or demonstrate specific behavior to encourage the user to be more physically active.⁶ Even though there's no agreement on the number of behavior-change techniques that are associated with achieving greater results, some techniques (including self-monitoring, performance feedback, and goal setting) are associated with being effective.^{1,7} Because those behavior-change techniques can be embedded in health apps and because interventions that include apps show promising results, we expect that apps are an effective way to promote physical activity. However, it remains unclear if existing apps are successful in achieving long-term behavior change.^{5,6}

Also, when taking a more technical perspective, it's clear that apps promoting physical activity don't make use of the full potential of mobile phone technology. A review of the features in smartphone apps that offer tailored support for physical activity show that a majority of the apps rely on manual user input as a data source (84 percent), and approximately half of the reviewed apps make use of built-in sensors (47 percent).⁸ The GPS sensor is most widely used (35 percent), while the accelerometer (10 percent) and other built-in sensors (5 percent), such as the camera, are less common. Almost two-thirds (62 percent) of the reviewed apps offer the user graphs of or calculations over the data, and more than 80 percent make a comparison with either goals, guidelines, or previous behavior. Although a majority of the apps (60 percent) facilitate support from peers or other users by providing a community, none of the apps provide support in the form of predictions or personal advice. Only one app

(1 percent) adapts to the user over time. These results show that some of the features are well-represented among current smartphone apps, but other possibilities are underused.⁸ This provides an opportunity for future research and development of apps to promote physical activity.

User Experience and Expectations

When developing a theory-based and effective app, users' preferences and opinions should be taken into account. So, before developing the Active2Gether system, we conducted two studies to assess the participants' preferences and expectations that we can integrate into the intervention.

In the first study, we asked 179 participants to complete an online survey to explore their preferences for behavior-change techniques in an app that promotes physical activity. In this study, we found that 94 percent of participants currently used a smartphone and apps in general, but 31.3 percent only sometimes used physical activity apps and 35.2 percent didn't use any physical activity app. In general, participants liked features that helped them set and review goals, and features that monitored and provided feedback on behavior. Among all the listed features, participants most liked features that targeted goal setting on the outcome of behavior, self-monitoring of behavior, and self-monitoring of the outcome of behavior. Participants mainly liked apps that combined self-monitoring and a personal coach – as a replacement for a human personal coach – followed by self-monitoring only ($N = 50$, 27.9 percent), and only a personal coach ($N = 18$, 10.1 percent). Only 6.1 percent ($N = 11$) were uninterested in any of these functions.

The second study had a qualitative design (that is, focus group discussions), to explore the respondents' preferences, attitudes, and experiences regarding physical activity apps. To ensure meaningful discussions, we asked the participants ($N = 30$) to download and use an existing app, so their experiences could serve as input for the discussions. We encouraged them to share their experiences and opinions. The results of these discussions are in line with the online survey. The participants preferred a personal (virtual) coach that helps the user set goals, while also supporting and motivating the user to achieve self-determined goals.⁹

Implications for the Active2Gether System

After conducting these two studies to assess user preferences and expectations, we discerned that

the Active2Gether system should mimic a personal coach that helps the user set goals, while also supporting and motivating the user to achieve these goals.⁹ From these two studies, we also drew a number of specific conclusions about desired functions of the Active2Gether system.

Self-monitoring features. When integrating self-monitoring features in the Active2Gether system, users prefer to monitor their self-set goals, behavior outcomes (such as weight or body-mass index), and actual behavior. Thus, users can monitor their behavior using a log book function (based on manual user input) using an activity monitor and GPS measurements. Because participants in the focus group discussions mentioned that a major drawback of using the GPS sensor is that it consumes batteries, we use a GPS app that only consumes batteries to a limited extent. The app and website show a simple and clear overview of daily activities and progress toward a goal, in accordance with the results from both studies.

Goal setting and coaching features. Existing physical activity apps differ in how users can set their own goals. Almost all participants that contributed to the focus group discussions preferred a virtual coach in combination with setting goals. Participants wanted to choose between different goals or be able to set a new goal. The app should replace a personal coach by reminding them to exercise or tell them about their progress. Participants repeatedly mentioned that it's important that the app makes a schedule, sets a task, and works toward the self-set goal.⁹ Therefore, the Active2Gether system offers the opportunity to choose a specific domain such as stair climbing, sports activities, and active transport to set your self-determined goals. In addition, the system helps set graded tasks to achieve the goal. Furthermore, there are weekly evaluations of the goals where users are asked to reset their own goals. Based on the self-determined goals, the user is coached to reach these goals. The system surpasses existing apps because coaching is based on the user's assessment of psychological determinants, a motivational state of mind, and the context (physical and social environment).

Social comparison and competition features. Although social support is positively associated with physical activity, participants in both studies

didn't like features that promoted social support in existing apps (for example, links to social network sites). Therefore, the Active2Gether system will influence the user's beliefs more implicitly by targeting important links in the user's social network (as we discuss later).

Some physical activity apps rank the user's results against other (anonymous) users. In the focus group discussions, most participants evaluated the ranking feature as interesting and motivating. Therefore, the Active2Gether system will enable social comparison by including such ranking features. However, some participants didn't like the ranking features, because they thought it was unimportant and they didn't perceive their physical activity as a game. Instead, they preferred to compare their results to their own previous behavior.⁹ Therefore, the system will offer the option to compare the user's current results with past results.

The Active2Gether System

To use the full potential of mobile technology for physical activity promotion, we propose a system that builds upon evidence-based theories and combines detailed behavior monitoring with intelligent data interpretation and model-based predictions of the effect of intervention strategies. We're currently developing the system.

The system consists of several components. An *activity monitor* continuously tracks the activity level during a day. A *smartphone app* monitors the user's actual location and makes it possible to present messages and questions to the user. The location data are used to trigger context-aware messages, but also to interpret the user's behavior (for example, determining what kind of transportation the user chose). Another component is a *website*, which provides an overview of the performed behavior, the messages to the user, and some representation of the activity of people in the user's social network. The smartphone app also displays this information. The final – and core – component of the system is a *reasoning engine*. This engine is built around a computational model of behavior change. By combining the data that has been collected via the monitoring components with information about the user's context, the reasoning engine determines which strategies will have the most positive effect on behavior.

System usage starts with a questionnaire about the user's personal situation that includes

questions about the characteristics of the home and work location, psychological factors such as perceived barriers, personal goals, and so on. This information forms the basis for personalization. After an initial monitoring phase, the system will coach the user on improving certain specific behaviors – that is, opting for active transport more often, taking the stairs instead of the elevator, or engaging in sports activities. The system does this by sending timely and context-specific personalized messages. After some time, the system revisits the focus of the coaching.

Integrating and Interpreting Data

One of the challenges in developing the Active2Gether system is to combine data from different sources and to interpret this meaningfully. The system automatically collects three types of dynamic data, namely GPS coordinates, step count data, and stair use data. We use this data to derive various kinds of other information, such as speed, distance traveled per time unit, frequently visited locations, activity level, and transportation mode.

One of the objectives of the Active2Gether system is to give personalized coaching not only based on an individual's behavior, but also on his/her physical and social environment and actual context. This requires information about, for example, whether a person is going to some frequently visited location, whether s/he is currently at work or near the sports club, and what type of traveling options s/he chooses. There are various kinds of input that we use in our system to provide personalized support. First, we monitor a user's activity, which includes step counts and stairs taken on a minute basis. To acquire this data, we employ a commercial activity monitor that captures the activity data by using a 3D accelerometer and an altimeter. The device is simple to use and the data is accessible through a Web service interface. The Web service provides these data through an OAuth1.0a mechanism. This means that our system can ask a user once for permission to access his/her activity data. We collect the data regularly and store a summarized version in our system's database. We use this data in several ways: for presenting the user's activity level, for determining the type of coaching, and for determining whether a person opted for active transport.

Another data type is collected by monitoring a person's location (GPS coordinates). We have at least two objectives for this. First, the location data are used to cluster different GPS coordinates

to determine the most frequently visited or significant locations (for example, home, study/work place, and a sports club). The purpose of detecting significant locations is to suggest personalized coaching messages. For instance, if the system is coaching a person to take the stairs more often, it's only useful to suggest this when s/he is at a location where that's an option. Similarly, it's only suitable to suggest that someone take active transport if the distance between two locations is limited. The other objective is to understand and detect the mode of transportation. This is achieved by combining several types of information: the speed between different significant locations, the registered activity level in that period, and the transportation option that a user has described in the initial questionnaire. Together, this lets us determine whether a person has taken active transport (bike or walk) or used nonactive modes of transportation, such as a car, tram, bus, or metro.

As an illustration, consider Figure 1. It depicts the activity and location data of a participant in a pilot study with the system. Figure 1a shows the traveling trajectory for the participant on a particular day. When translated into speed (see Figure 1b), we determine that the person starts traveling around 9:30 a.m. and reaches a destination around 10:15 a.m. We see that the speed during the considered period is quite high. Because we know that one of the transportation options is a bus, we conclude that the person didn't choose an active traveling option. Figure 1c shows the number of steps per minute. During the same traveling period, we see that the person's step count is low or zero.

The Reasoning Engine

One of the fundamental components of the Active2Gether system is the reasoning engine, which allows for analysis and interpretation of the user data and personalization of the coaching strategies. We split the reasoning process into four key parts: assessing the user's activity and awareness phase, detecting opportunities for improvement, selecting promising coaching strategies, and implementing coaching strategies. Here, we explain these four parts of the reasoning process in more detail.

Assessing the user. In the first step of the system's reasoning process, it assigns users to one of four categories. These categories represent different

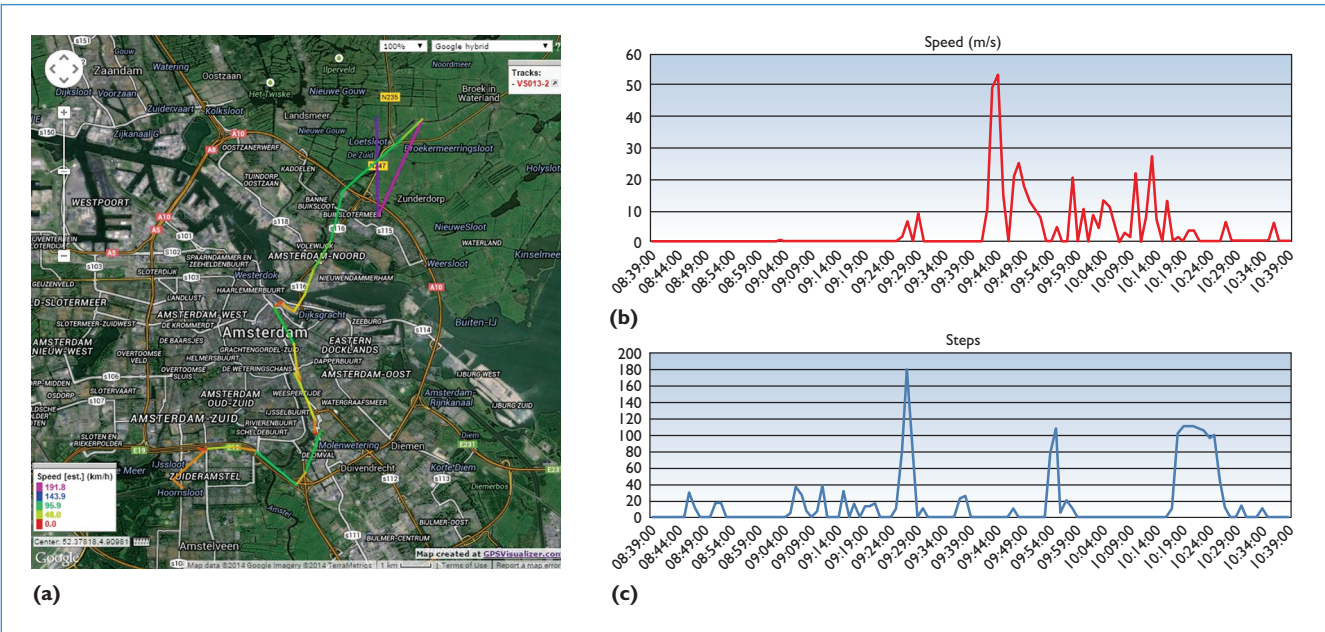


Figure 1. Location data and activity data of one of the participants. (a) Traveling trajectory for the participant on a particular day. (b) Speed in meters per second. (c) Number of steps per minute.

awareness states regarding their physical activity. The classification is based on two inputs: the objective evaluation of the user's physical activity level (whether the user meets the norm), and the subjective evaluation of the user's physical activity level (whether the user thinks that his/her lifestyle is sufficiently active). Table 1 summarizes the categories.

Based on this user categorization, different combinations of system modules (education, coaching, and feedback) are activated. These different user categories thus represent the first act of personalization in the Active2Gether intervention. Instead of treating all users the same, their specific needs and wishes are taken into account. This should lead to improved user acceptance and adherence, and consequently to increased intervening effectiveness.¹⁰

Detecting opportunities for improvement. The second step of the reasoning process is part of the system's coaching module. In this step, detailed information about the user's context and behavior is used to identify in which domains the user could be more physically active. These domains are parts of the user's daily life. They comprise stair use at significant locations (for example, home, work, and school), active transport to significant locations, and leisure-time sports activities.

By combining activity data and GPS data, we estimate the user's physical activity in each of these domains. These physical activity values are then compared to estimated maximum or ideal values, based on information about the user's context. For example, if a user works on the third floor, and on average climbs another three floors during the day, a total number of six floors during a work day would be reasonable. For a user that works on the second floor, but on average climbs another eight floors during a work day, a total number of six floors is comparatively low. Similar evaluations are developed for the physical activity level in active transport and sports activities. Using these evaluations, the system detects the domain with the largest potential for improvement. It then suggests these to the user as a focus for the coaching process, and asks the user to set a specific goal.

This relative evaluation of the user's behavior and the suggestion of a certain coaching domain represents the second act of personalization. It prevents the system from imposing the same expectations on all users.

Selecting promising coaching strategies. The third step of the reasoning process is part of the system's coaching module as well. Here, our approach investigates which coaching strategy yields the

Table 1. Categories based on objective and subjective evaluation.

No.	Objective	Subjective	User category
1	Insufficient	Sufficient	The user is unaware that s/he is insufficiently physically active, and will be <i>educated</i> to increase this awareness.
2	Insufficient	Insufficient	The user is aware that s/he is insufficiently physically active, and will be <i>coached</i> to increase his/her physical activity level.
3	Sufficient	Insufficient	The user is sufficiently physically active, but still wants to be <i>coached</i> to increase his/her physical activity level.
4	Sufficient	Sufficient	The user is sufficiently physically active, and wants to maintain his/her physical activity level. This user won't be coached to increase his/her physical activity level, but will receive <i>feedback</i> .

most promising effect on behavior. (Which specific domain of physical activity is coached is determined in the previous step of the reasoning process.) Most of the coaching strategies are predefined sets of messages that each target one or more personal determinants that govern the engagement in healthy behavior. The coaching strategies are based on established behavioral change techniques, such as prompting goal setting, providing information on consequences, and prompting barrier identification. The system estimates the effect of these coaching strategies on behavior based on simulations of a computational model that delineates the dynamics between these personal determinants.¹¹ The model is mainly based on the social cognitive theory, which describes the reasons why people fail or succeed to exhibit some desired (health) behavior from both social and cognitive determinants.^{12,13} We extend this model with concepts from other theories (such as self-regulation theory and the health-action process approach) and literature. The resulting model contains determinants such as intentions, self-efficacy, and outcome expectations.

In this process, the system first estimates the states of personal determinants by means of short questions posed and answered via mobile phone. The resulting values are used as input for the computational model. In the simulation of each of the possible coaching strategies, one of the values of the determinants is changed according to the expected effect of the strategy under consideration. Then, the system uses the computational model to simulate the effect on the behavior. After simulating all possible coaching strategies, the most promising one is selected for implementation. This cycle is repeated weekly, to tailor to the user's strongest psychological needs at all times.

In contrast to the relative evaluation of the user's behavior, this third act of personalization doesn't tailor the intervention based on information about the user's environment, but rather on information about his/her motivational state of mind. This way, users receive support on the aspects that are relevant to their motivation and behavior.

Implementing coaching strategies. The fourth step in the reasoning process is related to implementing the selected coaching strategies: once the system selects the most promising strategy, it's put into practice, so that the user can benefit from the motivational support that the system offers. The specific procedure of executing the coaching strategy depends largely on its type: each type of coaching requires a different approach. For example, to give the user more profound insight into his/her own behavior, detailed overviews of past activities and progress can be shown prominently in the app or on the website. Alternatively, the most common type of coaching strategies, namely the sets of supportive messages, are carried out by a process that selects and sends the messages to the user at the right moment. Selecting the set of messages (each targeting a different personal determinant) depends on the simulations of the computational model. An example of a supportive message that aims to increase self-efficacy by means of prompting the user to set a goal is "Hey #username! To become more active, it helps to set clear goals. What is your goal for this week?"

An example of coaching strategies that require quite extensive reasoning are social network interventions. These interventions are based on the social circle of a person – this circle is believed to play an important role in the adoption

of certain health behaviors. In the Active2Gether intervention, this social network is used to influence the user's attitude about physical activity. Based on theories of social contagion, we can predict what could be the effect of changing the structure of the social network on the contagion of attitudes about physical activity. More specifically, we would want to strengthen ties with parts of the social network that are physically active and weaken ties with people with a negative attitude toward physically active behavior.¹⁴ By selectively showing information about other users in the system, we try to influence the connection strengths in the social network, to optimize the contagion of attitudes between specific people.

Promoting physical activity is a public health priority in most Western countries, and mobile technology provides seemingly useful ingredients for automated personalized coaching to improve physical activity. However, the effectiveness of interventions based on mobile technology hasn't been proven yet. Here, we described the design and ingredients of a mobile system for physical activity promotion based on ongoing research about elements of technology-based physical activity promotion. By taking user expectations and theory-based coaching strategies as a basis for system interaction, we aim at an effective and engaging system. In addition, by combining novel approaches for context detection and interpretation with model-based prediction of the effectiveness of strategies on behavior change, the Active2Gether intervention truly is personal. In this way, the Active2Gether system aims to surpass existing physical activity apps, as it uses more of the potential that mobile technology offers. Soon we'll evaluate the Active2Gether system's effectiveness in a real-life trial. □

Acknowledgment

The authors contributed equally to this work.

References

1. V.S. Conn, A.R. Hafdahl, and D.R. Mehr, "Interventions to Increase Physical Activity among Healthy Adults: Meta-Analysis of Outcomes," *Am. J. Public Health*, vol. 101, no. 4, 2011, pp. 751–758.
2. R.M. Eime et al., "A Systematic Review of the Psychological and Social Benefits of Participation in Sport for Adults: Informing Development of a Conceptual Model of Health through Sport," *Int'l J. Behavioral Nutrition and Physical Activity*, vol. 10, Aug. 2013; www.ijbnpa.org/content/10/1/98.
3. I.M. Lee et al., "Effect of Physical Inactivity on Major Non-Communicable Diseases Worldwide: An Analysis of Burden of Disease and Life Expectancy," *Lancet*, vol. 380, no. 9838, 2012, pp. 219–229.
4. P.C. Hallal et al., "Global Physical Activity Levels: Surveillance Progress, Pitfalls, and Prospects," *Lancet*, vol. 380, no. 9839, 2012, pp. 247–57.
5. A. Middelweerd et al., "Apps to Promote Physical Activity among Adults: A Review and Content Analysis," *Int'l J. Behavioral Nutrition and Physical Activity*, vol. 11, July 2014; www.ijbnpa.org/content/11/1/97.
6. D.E. Conroy, C.H. Yang, and J.P. Maher, "Behavior Change Techniques in Top-Ranked Mobile Apps for Physical Activity," *Am. J. Preventive Medicine*, vol. 46, no. 6, 2014, pp. 649–652.
7. S. Michie et al., "Effective Techniques in Healthy Eating and Physical Activity Interventions: A Meta-Regression," *Health Psychology*, vol. 28, no. 6, 2009, pp. 690–701.
8. J.S. Mollee, "Active2Gether: Encouraging Physical Activity among Adolescents," master's thesis, Dept. of Artificial Intelligence, VU Univ. Amsterdam, 2012.
9. A. Middelweerd et al., "What Features Do Dutch University Students Prefer in a Smartphone Application for Promotion of Physical Activity? – A Qualitative Approach," *Int'l J. Behavioral Nutrition and Physical Activity*, vol. 12, Mar. 2015; www.ijbnpa.org/content/12/1/31.
10. W. Kroeze, A. Werkman, and J. Brug, "A Systematic Review of Randomized Trials on the Effectiveness of Computer-Tailored Education on Physical Activity and Dietary Behaviors," *Annals of Behavioral Medicine*, vol. 31, no. 3, 2006, pp. 205–223.
11. J.S. Mollee and C.N. van der Wal, "A Computational Agent Model of Influences on Physical Activity Based on the Social Cognitive Theory," *PRIMA 2013: Principles and Practice of Multi-Agent Systems*, Springer Science Business Media, 2013, pp. 478–485.
12. A. Bandura, "Health Promotion by Social Cognitive Means," *Health Education & Behavior*, vol. 31, no. 2, 2004, pp. 143–164.
13. A. Bandura, "Health Promotion from the Perspective of Social Cognitive Theory," *Psychology & Health*, vol. 13, no. 4, 1998, pp. 623–649.
14. M.C.A. Klein et al., "Effect of Changes in the Structure of a Social Network on Emotion Contagion," *Proc. 2014 IEEE/WIC/ACM Int'l Joint Conf. Web Intelligence (WI) and Intelligent Agent Technologies (IAT)*, 2014, pp. 270–277.

Michel C.A. Klein is an assistant professor in the Department of Artificial Intelligence at VU University Amsterdam. His research interests include


technology that's able to interpret human behavior and provides personalized and contextualized support. Klein has a PhD in artificial intelligence from the VU University Amsterdam. Contact him at michel.klein@vu.nl.

Adnan Manzoor is a PhD candidate in the Agent Systems Research group of the Department of Artificial Intelligence at VU University Amsterdam. His research interests include computational modeling of cognitive and affective processes, and the role of these processes in the context of a person's social network both for purposes of monitoring and support via mobile phone apps. Manzoor has an MS in information technology from QUEST, Nawabshah. Contact him at a.manzoorrajper@vu.nl.

Anouk Middelweerd is a PhD candidate at the Department of Epidemiology and Biostatistics at the VU University Medical Center. Her research interests focus on *healthy lifestyles and public health, with special attention to physical activity promotion*. Middelweerd has an MS in health sciences – prevention and public health from VU University Amsterdam. She's a member of the International Society of Behavioral Nutrition and Physical Activity. Contact her at a.middelweerd@vumc.nl.

Julia S. Mollee is a PhD candidate in the Agent Systems Research group of the Department of Artificial Intelligence at the VU University Amsterdam. Her research interests focus on the development of intelligent coaching systems that support people in making healthy lifestyle choices. Mollee has an MS in artificial intelligence from VU University Amsterdam. Contact her at j.s.mollee@vu.nl.

Saskia J. te Velde is an assistant professor at the Department of Epidemiology and Biostatistics at the VU University Medical Center. Her main research interests are in social and psychological influences on lifestyle and public health, combined with a strong interest in the related methodology and statistical analyses of data. Te Velde has a PhD in epidemiology from the VU University Amsterdam. She's a member of the International Society of Behavioral Nutrition and Physical Activity, the Dutch Society for Human Movement Science, and the Dutch Society for Epidemiology. Contact her at s.tevelde@vumc.nl.

 Selected CS articles and columns are also available for free at <http://ComputingNow.computer.org>.

ADVERTISER INFORMATION

Advertising Personnel

Marian Anderson: Sr. Advertising Coordinator
Email: manderson@computer.org
Phone: +1 714 816 2139 | Fax: +1 714 821 4010

Sandy Brown: Sr. Business Development Mgr.
Email: sbrown@computer.org
Phone: +1 714 816 2144 | Fax: +1 714 821 4010

Advertising Sales Representatives (display)

Central, Northwest, Far East:
Eric Kincaid
Email: e.kincaid@computer.org
Phone: +1 214 673 3742
Fax: +1 888 886 8599

Northeast, Midwest, Europe, Middle East:
Ann & David Schissler
Email: a.schissler@computer.org, d.schissler@computer.org
Phone: +1 508 394 4026
Fax: +1 508 394 1707

Southwest, California:
Mike Hughes
Email: mikehughes@computer.org
Phone: +1 805 529 6790

Southeast:
Heather Buonadies
Email: h.buonadies@computer.org
Phone: +1 973 304 4123
Fax: +1 973 585 7071

Advertising Sales Representatives (Classified Line)

Heather Buonadies
Email: h.buonadies@computer.org
Phone: +1 973 304 4123
Fax: +1 973 585 7071

Advertising Sales Representatives (Jobs Board)

Heather Buonadies
Email: h.buonadies@computer.org
Phone: +1 973 304 4123
Fax: +1 973 585 7071